Context-aware Support for Cardiac Health Monitoring using Federated Machine Learning

Godwin Okechukwu Ogbuabor[1], Juan Carlos Augusto[1], Ralph Moseley[1], and Aléchia van Wyk[2]

[1] Research Group on Dev. of Intelligent Environments, Middlesex University London
go314@live.mdx.ac.uk, (j.augusto,r.moseley)@mdx.ac.uk
[2] Department of Natural Sciences, Middlesex University London, UK
a.vanwy@mdx.ac.uk

Abstract. Context-awareness provides a platform for healthcare professionals to assess the health status of patients in their care using multiple relevant parameters such as heart rate, electrocardiogram (ECG) signals and activity data. It involves the use of digital technologies to monitor the health condition of a patient in an intelligent environment. Feedback gathered from relevant professionals at earlier stages of the project indicates that physical activity recognition is an essential part of cardiac condition monitoring. However, the traditional machine learning method of developing a model for activity recognition suffers two significant challenges; model overfitting and privacy infringements. This research proposes an intelligent and privacy-oriented context-aware decision support system for cardiac health monitoring using the physiological and the activity data of the patient. The system makes use of a federated machine learning approach to develop a model for physical activity recognition. Experimental analysis shows that the federated approach has advantages over the centralized approach in terms of model generalization whilst maintaining the privacy of the user.

Keywords: Cardiac Monitoring · Context-Awareness · Federated Learning.

1 Introduction

Cardiac diseases such as arrhythmia, stroke, and coronary heart disease (CHD) has been shown to be managed by monitoring patients' physiological signals in real-time. The symptoms of these diseases are diverse, ranging from minor chest palpitations, chest pain, fainting(syncope) to sudden heart attack, depending on the type and severity of the heart disease [22]. Fortunately, with the most recent advances in ECG monitoring and the help of modern mobile phone technology, monitoring a patient in the remote areas has become easier and more accessible [26]. However, it is essential to note that to predict abnormalities, a specific vital sign such as heart rate, ECG signals may not provide sufficient knowledge to assist physicians in decision-making [20]. The combination of physiological parameters, environmental information, and patients activities can go a long way in providing a rich platform, that will enable physicians timely decisions; thereby, offering better environment for healthcare delivery services [25].

Context-awareness is an important part of systems implemented in areas such as Intelligent Environment, Ambient Intelligence, Pervasive and Ubiquitous Computing [3]. The fundamental idea behind context-awareness in healthcare is to develop a proactive and efficient system, that can correlate patient's contextual information and adapt to the changes in the patient's condition and environment [21]. Context-awareness is the ability of a system to use contextual information to provide services that are relevant to the stakeholders based on their preferences and needs while context is "the information which is directly relevant to characterize a situation of interest to the stakeholders of a system" [5]. It plays an essential role in the healthcare delivery decision-making process and assists physicians to properly and timely monitor patients in their care. This research presents a context-aware decision support system for cardiac condition monitoring and management during rehabilitation (mCardiac). The system makes use of federated machine learning approach for activity recognition to maintain users' privacy. Federated learning is a machine learning technique that allows different clients from different locations to collaboratively learn a machine learning model without sending their data to a central server. The formulated scenario below was used to help understand the proposed system in a real working environment.

Scenario: Mike was recently discharged from hospital after suffering from Coronary Heart Disease(CHD). In order to avoid cardiac readmission, his physician, Dr. Charles needs to keep in touch with him regularly. However, Mike lives about 20 miles from the hospital, therefore creating a barrier for a constant visit to the hospital. In order to frequently monitor Mike's health status and offer personalized recommendations, Dr. Charles needs a platform that will generate and correlate Mike's physiological signals and activity details from distance. The proposed system will collect, aggregate and process Mike's contextual information and present it as a decision support tool.

An intelligent analysis of mike's contextual information will assist Dr. Charles in the decision-making process and offer a better platform for healthcare delivery services. It will enable Dr. Charles to understand the daily activity pattern of Mike, the change in daily behavior, change in physiological information, and its effects on the recovering process.

The rest of the work is organized as follows: Works by other researchers is presented in section 2, discussing their strengths and limitations. In section 3, the research presents the context-aware decision support system, discussing the methodology used, federated approach, activity recognition process, and the experimental analysis, while section 4 presents the system evaluation and results of the experimental analysis. Finally, section 5 shows the conclusion of the work and possible future directions.

2 Related Work

Most of the studies on cardiac condition monitoring focus on identifying irregularities in a specific vital sign [16]. This approach might not provide enough information for effective and efficient cardiac condition monitoring. Recently, some researchers proposed context-aware systems for cardiac patient monitoring, however, research in this area requires significant improvements. Li et al. [11] developed a system that records biosignal of the patients and request for context information when there is an abnormality. The patient has to input information about his/her daily life activities. So this system is not fully automatic since it requires user's intervention. The focus of Forkan and Hu [8] was on the older adult, they developed a cloud-based system that extracts health parameters from Fitbit device and ECG sensors. The context information of the patient is sent via social media to the patient's doctor, relative, or friends when there are abnormal changes. They used the Fitbit device to collect the activity details of the user. However, this device could only recognize the steps of the subject and cannot show specific activities performed such as walking, running, and sitting.

Sannino et al. [18], introduced an "intelligent mobile system based on rule decision support system for cardiac patients". The system correlates data from the ECG sensor with physical activities such as walking, running, and body posture. They used the threshold rule to determine the activity of the patient and argued that testing the system with fifteen healthy persons proved the effectiveness of the proposed approach. Kunnath et al. [10] also used the threshold approach to detect different activities (Lying, Standing, Walking, Jogging) for cardiac disease monitoring and claimed a classification accuracy of 94%. Though the approach shown to be effective, however, using a threshold rule to determine the activity of the user might not be the best option because of the wide range of physical activities, coupled with the disparity in how a specific activity is to be performed.

Another similar solution was presented by [14], they combined the ECG signals with physical activities for cardiac disease diagnosis. Miao et al. [14] applied machine learning technique to recognize human activities. Machine learning provides computation methods and learning mechanisms for developing a model to predict a situation based on the ground truth. They recruited seven healthy people who wore ECG sensors on their chest and carried smartphones in their pockets to collect sensor data. Each subject was asked to perform three different activities (Running, Rest and Walking). The sensor data from the seven participants were aggregated, processed, and used to train J48 decision tree algorithms in order to predict the activity of the users when new data without ground truth are fed into the model.

3 Decision Support System for Cardiac Condition Monitoring

Decision Support Systems(DSS) are computer applications developed to assist clinicians in decisions making for patient wellbeing. Such systems range from simple software to complex artificial intelligence applications. The importance of context-aware DSS is revealed by the knowledge gained by the combination of multiple sources of information to provide better insight and understanding of the situation under consideration. A context-aware DSS for cardiac condition monitoring and management during rehabilitation is presented. The system will utilize the patient's contextual information from different sources to provide a useful tool to physicians. This will enable the healthcare professional to make better decisions to avoid cardiac readmission or perhaps death.

This research considers the ECG signals from the Holter monitor, activity data from smartphones, and time of the day as essential sources of information to provide an effective and efficient system for cardiac rehabilitation monitoring. These sources of information are selected based on interviews with the healthcare professionals and the quest to present a real-time, reliable, and energy-efficient system. The system involves data collection from Holter monitor and smartphone sensors, machine learning algorithm training for activity recognition and pattern discovery, and finally, implementation of a decision support tool. During the monitoring process, the subject will be required to carry a smartphone running our mobile app for data collection and a Holter monitor for ECG signals recording. Holter monitor is a portable and continuous monitoring device used to generate and record ECG signals [15]. Some of the modern Holter monitors allow users to wear the device while doing their normal activities. Smartphone is equipped with an accelerometer sensor that generates data regarding the movement of the user.

3.1 Architecture of the Proposed System

The proposed architecture shown in figure 1 is made up of the following features: (i) Context acquisition, (ii) Context modeling and storage (iii) Context reasoning and visualization, and (iv) Personalized recommendation. During the monitoring process, the subject will be required to carry a smartphone running the mobile app to collect accelerometer sensor data and a Holter monitor to record ECG signals, this forms the context acquisition unit. Then, at the modeling and storage stage, the acquired contexts will be presented in an efficient and structured format and stored in a database for retrieval; while at the context reasoning and visualization stage, relevant features will be extracted from the context data and analyzed for knowledge discovery. Also at this stage, the outcome of the analysis will be presented as a decision support tool. Finally, healthcare professionals will be able to offer personalized recommendations to the patient based on the contextual analysis. These recommendations could be in the form of text or auditory format regarding the health condition.

3.2 Methodology

The User-Centred Intelligent Environments Development Process (UCIEDP) was adopted for this research [4]. The stakeholders are at the heart of this methodology, hence making it crucial to involve the healthcare professionals at

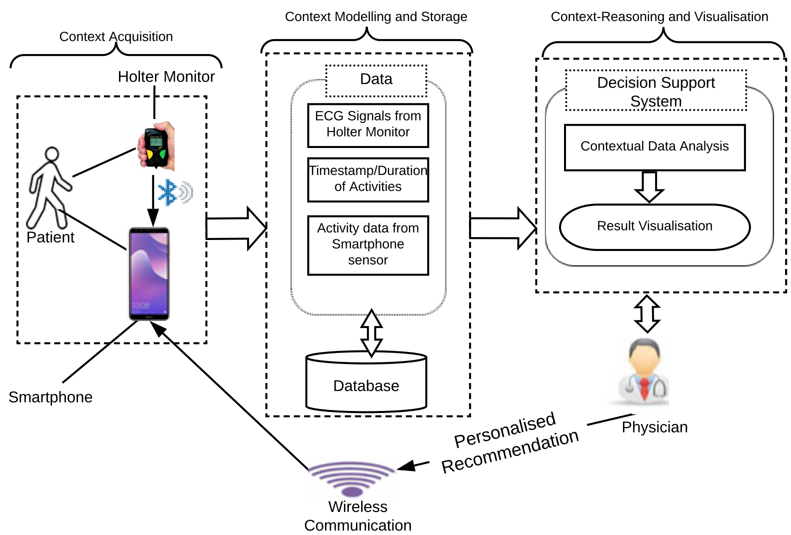

Fig. 1: Proposed context-aware system architecture

the early stage of this work. As part of the process interview was conducted with a cardiologist and a cardiac rehabilitation nurse to gather user requirements. The outcome of the interview reveals that physical activity recognition is an essential part of cardiac condition monitoring especially during rehabilitation, this leads to the next stage, activity recognition. A mobile application was developed to collect accelerometer sensor data [17], participants recruited for the experiment, and the data used to train machine learning algorithms for activity recognition. Federated machine learning technique was used to develop a model to predict the activity of the user when sensor data without ground truth is fed into the model. Finally, the results of the experiments presented for knowledge discovery and personalized recommendations.

3.3 Federated Learning

Federated learning (FL) is a decentralized model training approach that allows different clients in different locations to collaboratively learn a machine learning model without transferring dataset that may contain private information to a central server [12]. FL has been applied in different domains ranging from health-care, IoT, transportation, mobile apps, defense [2]. The difference between the centralized approach and the FL approach is that in the centralized approach, the individual dataset is sent to the server where the machine learning model is developed. The aggregated data is used to train the machine learning model and each user can access the model by connecting to the server. While, in the FL approach, each client train the model using their private data, the parameters are sent to the server for aggregation. Data is kept in each client domain and knowledge is shared through an aggregated models [1]. Figure 2 shows the architecture of the FL technique while figure 3 shows the architecture of the centralized learning technique. There are about four steps to the development of a

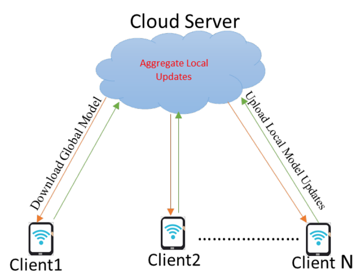

Fig. 2: Federated Architecture

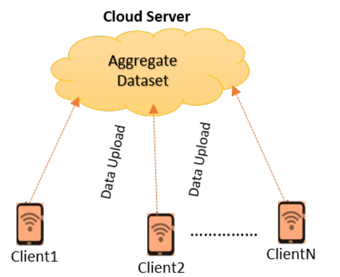

Fig. 3: Central Architecture

FL model [2]. a) Develop and train the model using a publicly available dataset. It is assumed the dataset can be used without privacy concerns. b) A copy of the global model is sent to different clients and they train the copy of their model using their private dataset. c) Then, each of the clients sent the updated model to the server without sharing their dataset, only parameters are shared. d) The server aggregates the parameters from different clients and generates a new model. The new model then distributed to the participating clients. The most widely used technique for FL is federated averaging [13]. In this approach, the weights(learning parameters) of the models from the clients are averaged to provide a new weight leading to a new model.

3.4 Activity Recognition

Recognizing human activities such as walking and running or human-related actions aims to observe and understand what type of activities or routines performed by the subject at time-interval [24]. The work in [19] pointed out that the primary focus of cardiac rehabilitation is on exercise and needs to be automated. The built-in accelerometer sensor in modern Smartphones has made it possible to dynamically detect the activity of the user. To recognize the user's activity, he/she need to carry the mobile phone while doing daily activities. The first phase of the activity recognition is data collection using a mobile app, mobile phone was selected for the research because of its convenient and a large number of the population have smartphone with accelerometer sensor. The mobile app collects the A_x, A_y, A_z axis, and the corresponding timestamps. Secondly, the sensor data are processed and partitioned into equal groups at time-interval representing the segmentation stage. In the third stage, time or frequency domain features are extracted from each group, and finally, the extracted features are used to train machine learning algorithms in order to classify new data without ground truth. Algorithms 1 shows the process of activity recognition using centralized approach. The process starts by aggregating data from different clients $K = k_1, k_2, ...k_n$. The aggregated data is partitioned into windows w and features F_i extracted. The extracted features are used to train machine learning algorithms using the training dataset, $Ftrain$. Finally, the model evaluated using the test dataset, $Ftest$ and the accuracy returned.

Algorithm 1 Activity Recognition Process for Centralized Learning

1: **Input:** $D = A_x, A_y, A_z, M_g$
2: **Output:** Predicted Activities
3: Aggregate data D_k from clients $(k_1, k_2, \dots\dots\dots k_n)$
4: Partition D_K into sliding windows (w)
5: **for** each w in D_K **do**
6: Extract features $F_i = f_1, f_2 \dots\dots\dots\dots f_j$
7: Split F_i into Train($Ftrain$) and Test($Ftest$) sets
8: Train algorithm with $Ftrain$
9: Predict activity with $Ftest$
10: $results$ = accuracy(Predicted activities)
11: Return $results$

3.5 Experimental Analysis

To demonstrate the FL approach samples of accelerometer data from twelve volunteers [7] were used. The participants were asked to put the mobile phone running our data collector app in the pocket and perform four activities; sitting, walking, jogging, and standing. However, some of the participants was able to perform only three activities; Sitting, Standing and Walking. The mobile app collects the A_x, A_y, and A_z axis along with the timestamps at a frequency of 50Hz. Figure 4 shows the samples of the dataset collected from one of the participants for sitting and standing activities. The x-axis captures the horizontal movement of the smartphone, y-axis indicates the upward/downward movement of the phone while z-axis shows the forward/backward movement of the mobile device [6].

Activity	X-axis	Y-Axis	Z-axis	Timestamp
Sitting	1.283331	3.091009	9.083879	06/01/2021 10:16:48
Sitting	1.781341	3.03594	9.27542	06/01/2021 10:16:48
Sitting	1.755004	3.141289	9.124581	06/01/2021 10:16:48
Sitting	1.431776	3.122134	8.818114	06/01/2021 10:16:48
Sitting	0.794899	3.541133	8.834874	06/01/2021 10:16:48
Sitting	1.343188	3.526767	7.14691	06/01/2021 10:16:48
Sitting	2.092596	3.462122	7.010437	06/01/2021 10:16:48
Sitting	1.230657	3.447756	8.786988	06/01/2021 10:16:48
Sitting	1.283331	3.677606	8.528407	06/01/2021 10:16:48
Sitting	1.091789	3.668029	8.870789	06/01/2021 10:16:48
Standing	-1.75979	4.575459	6.402291	06/01/2021 10:19:30
Standing	-1.15404	5.339233	9.040782	06/01/2021 10:19:30
Standing	-0.61772	4.73827	9.96976	06/01/2021 10:19:30
Standing	-0.24182	4.223501	8.461368	06/01/2021 10:19:30
Standing	-0.26337	3.972102	7.503657	06/01/2021 10:19:30
Standing	-0.81405	4.16125	8.150111	06/01/2021 10:19:30

Fig. 4: Samples of the dataset

The magnitude of the three axes was computed to handle orientation problems of the smartphones making it four features; A_x, A_y, and A_z and magnitude.

The magnitude (m_g) of the total acceleration is computed by the square root of the sum of the squared acceleration of three axes in equation (1).

$$M_g = \sqrt{(A_x)^2 + (A_y)^2 + (A_z)^2} \tag{1}$$

Sliding window techniques were used to partition the sensor data into 4 seconds equal windows and extracted some time-domain features from each segment. For a given time series $[x_1, x_2, x_3, ..., x_n]$, n represents the total number of samples in each window segment, then features were extracted from each window. Table 1 presents the extracted features for the analysis. Each feature represents an input vector used for the algorithm training. The participants were grouped into four different groups, each group having participant(s) that performed the four activities (Sitting, Standing, Walking and Jogging) and assumed each group to be a client hence having four clients for the experiment. The distribution of samples collected from the groups is presented in table 2.

Table 1: Extracted features for algorithm training

Feature	**Equation**
Mean	$mean = \frac{1}{n}\sum_{i=1}^{n} x_i$
Variance	$var = \frac{1}{n}\sum_{i=1}^{n}(x_i - mean)^2$
Standard Deviation	$std = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - mean)^2}$
Minimum Value	$min = MIN(x_i)$
Maximum Value	$max = MAX(x_i)$
Median value	$median = \frac{n+1}{2}$
Standard Error of the Mean(sem)	$sem = \frac{std}{\sqrt{n}}$

Table 2: Distribution of samples from the users

Activities	**Client1**	**Client2**	**Client3**	**Client4**
Sitting	21649	32045	19192	14411
Standing	16203	28028	20184	11262
Walking	20470	33160	13821	16200
Jogging	5320	6253	6363	15868

Model Development and Aggregation: Two machine learning algorithms (Support Vector machine and Logistic Regression) were used in demonstrating the FL approach. The regularisation parameter in Support Vector Machine (SVM) and the inverse of the regularisation parameter in Logistic Regression (LR) was used as the learning parameters for the experiment. The regularization parameter shows how much the algorithm will focus to minimize misclassification.

Support Vector Machine: SVM is a supervised machine learning technique that discriminates between two classes by generating a hyperplane that optimally separate the classes. It uses machine learning techniques to maximize classification accuracy while automatically avoiding model overfitting [9]. The algorithm makes use of nonlinear function known as kernels to transform the input data into a multidimensional space [23].

Firstly, a global model was developed using the default parameters provided by Sklearn library in python and dataset from four of the participants. It is assumed that the dataset from the four participants could be used without privacy concerns. Secondly, the optimal value of the learning parameter using each client's dataset was searched. With the help of the gridsearchcv library in python, the optimal parameter was gotten from each client. Figure 5 shows the results of the parameter turning for the four clients. The upper line shows the training score while the lower line indicates the cross-validation scores using 10-fold cross-validation. The optimal parameter for client1 was found at $P_l = 3$, client2 at $P_l = 5$, client3 at $P_l = 1$ and client4 at $P_l = 9$. The optimal parameters were aggregated, the average computed and the result used to update the global model. Evaluating the new model using a new dataset that was not part of the training dataset, gave classification accuracy of 89%.

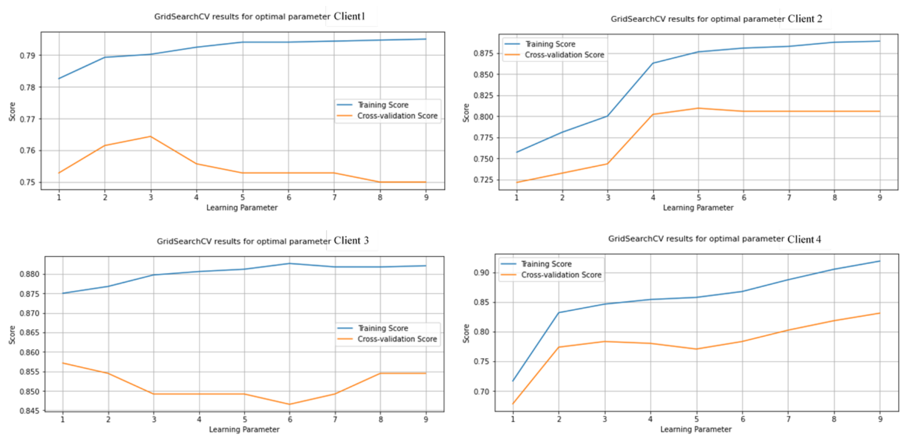

Fig. 5: Results of the learning parameter search using support vector machine

Logistic Regression: LR is a parametric algorithms in that it summarizes data with a set of parameters of fixed sizes independent of the number of training dataset. The same principle used in SVM was applied here for model development and aggregation. Other parameters were kept constant using Sklearn library in python while searching for the optimal value of the learning parameter(P_l). Figure 6 shows the results of the parameter turning using LR. The optimal parameter for client1 was found at $P_l = 9$, client2 at $P_l = 2$, client3 at $P_l = 8$ and client4 at $P_l = 6$. The parameters were aggregated and the average computed and used to update the global model. The updated model gave classification accuracy of 81% which is relatively lower than the performance of SVM with 89% accuracy.

The algorithm 2 shows the federated machine learning process for the activity recognition. The algorithms start by developing a global mode m. Then the model distributed to different clients $k = k_1, k_2, ...k_n$. Each client extract

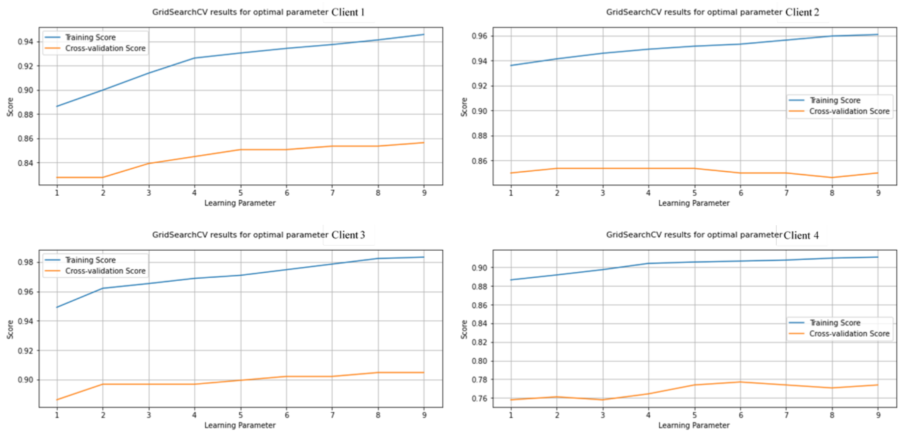

Fig. 6: Results of the learning parameter search using logistic regression

features $F_i = f_1, f_2 ... f_j$ from their dataset. The extracted features was used to obtain the optimal learning parameter P_l using GridSearchCV library. The values of P_l are aggregated from different clients and the average computed and used to update the global model.

Algorithm 2 FederatedAveraging for activity recognition. The K is the number of clients and P_l is the learning parameter

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Input D = A_x, A_z, A_y, M_g
Develop global model m
Distribute m to clients K
for each client in K = k_1, k_2, ......... k_n do
    Partition D_K into sliding windows (w)
    for each w in D_K do
        Extract features F_i = f_1, f_2 ............ f_j
    Search for optimal P_l
Aggregate P_l and compute average avg(P_l)
Update model m
```

Model Generalization: In centralized learning, each client is required to transfer their dataset to a central server. However, clients might not be happy to send their dataset due to privacy concerns. This often results in developing a model that overfits, hence does not generalize to the population due to insufficient amount of training dataset. Generalization is the ability of a machine learning model to correctly classify data, not in the training dataset. The research investigates the performance of the LR model using each client dataset assuming that some subjects are not happy to send their data due to privacy concerns. Table 3 shows the training and testing score for each client when the new dataset that was not part of the training set is used for validation. It is evident from the results that most of the clients recorded low testing score due to poor model generalization compared to the federated approach which recorded 81% accuracy.

Table 3: Model performance using each client dataset

	Client1(%)	**Client2(%)**	**Client3(%)**	**Client4(%)**
Train Score	88	93	95	89
Test Score	64	53	88	58

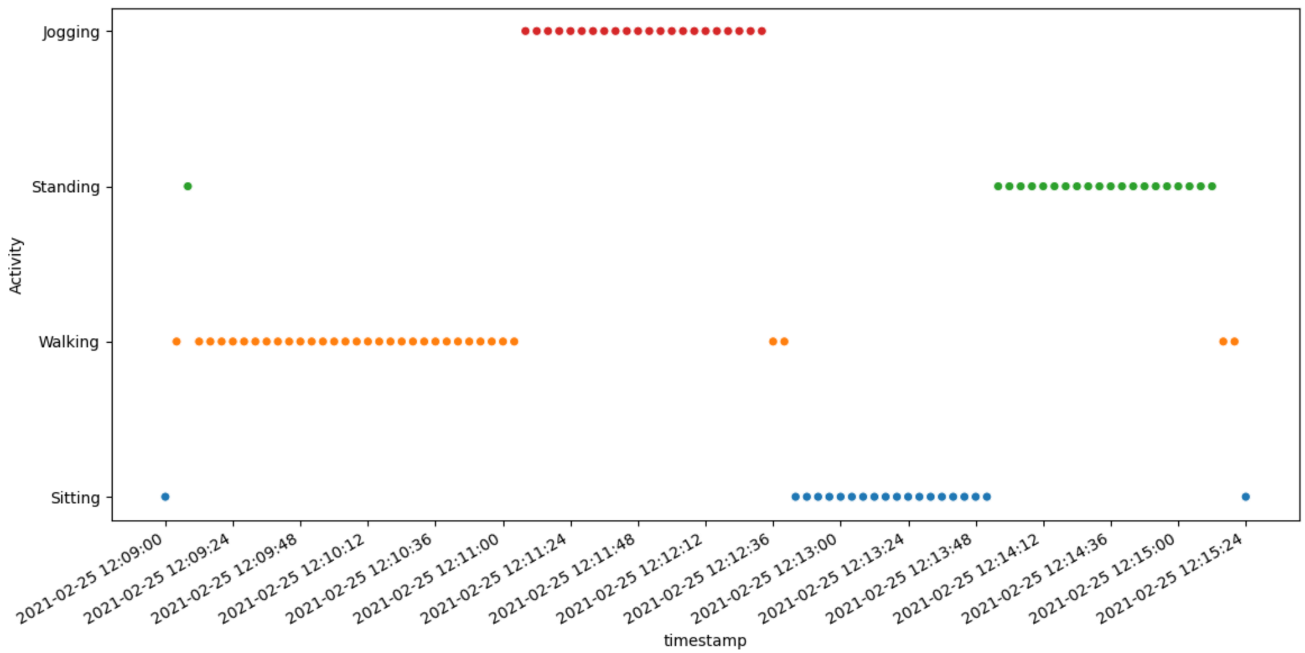
3.6 Benefits of the federated approach

In FL approach, dataset that may contain client sensitive information is not required to be transferred to a central server, only trained models are sent to the server for aggregation. This approach will enable several clients from different locations to participate in the algorithm training, hence better generalization while maintaining clients privacy.

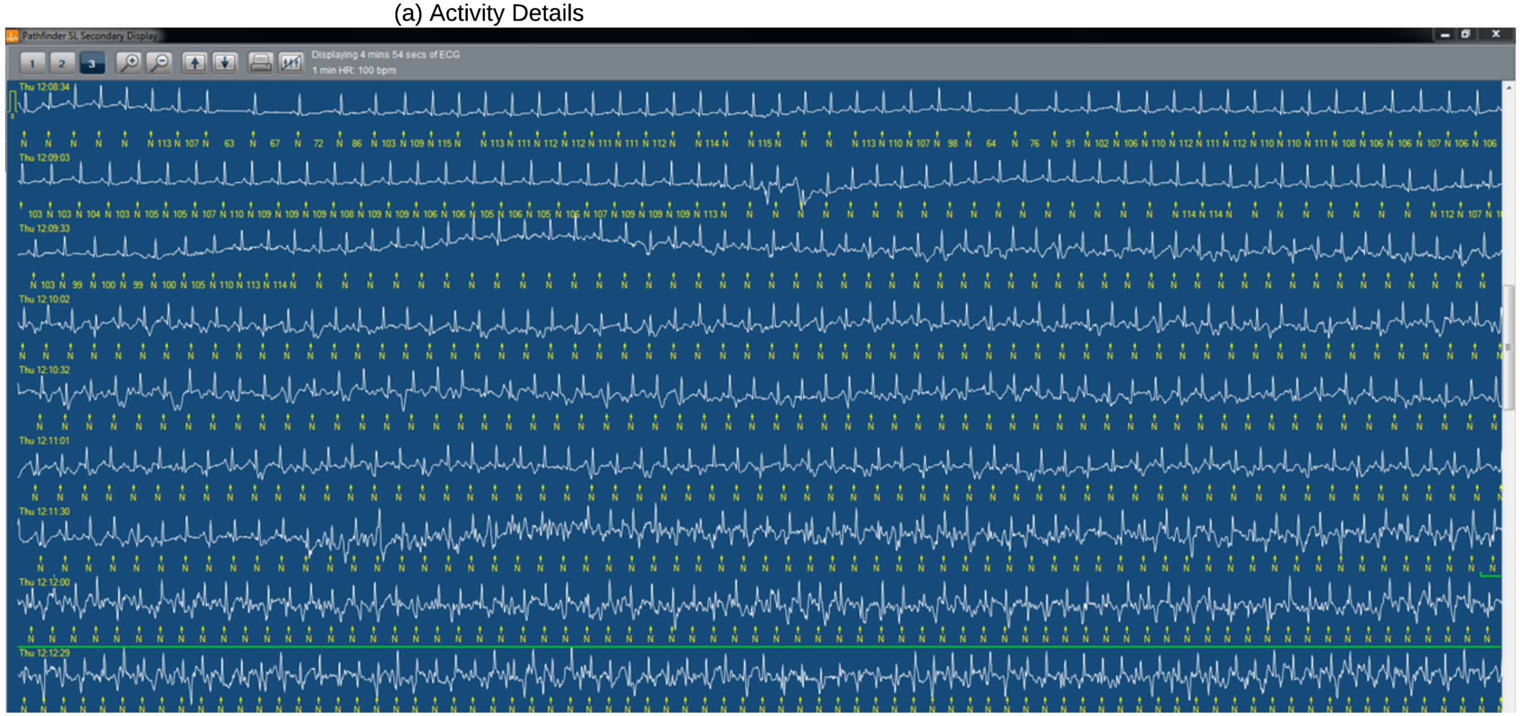
Another advantage of federated learning over centralized learning is that the centralized approach entails that a huge amount of storage capacity is required as well as sophisticated security protocols to avoid violation of the right to data, while in federated learning, only trained model is sent to the server which is not heavy compare to the dataset, and the security required to protect model is not as demanding as for datasets.

4 System Evaluation and Results

To evaluate the system, some of the participants used Holter monitors and smartphone running the mobile app concurrently for data collection. The Holter monitor used is “Lifecard CF” and the mobile app is available in google play store as “MCardiac”. The generated raw sensor data were processed and the federated model from SVM used to predict the activities of the user. This model was selected due to better performance. Figure 7, shows the graphical representation of the (a) activity information from smartphones and (b) ECG signals from the Holter monitor, from one of the participants. The information from the Holter monitor represents the heartbeat at time interval while the information from the smartphone shows the activity of the user at a time interval. The concept is to enable healthcare professionals to understand the activity of the patients when reading the ECG signals. If there are any irregularities in the signals, the health professional can consider the activity of the subject as a guide in decision-making. For instance, if the wave of the ECG signals is high, and the activity of the user is sitting. The physician might consider it as an abnormality, however, if the wave of the ECG signals is high and the activity jogging, he might argue that the increase in the signals wave might be due to the subject doing a rigorous activity. The system will enable the physician to offer the right advice to the patient instead of prescribing unnecessary medications.



(a) Activity Details



(b) ECG Signals

Fig. 7: System Output Showing (a) the Activity Details and (b) the ECG signals

5 Conclusion

Health monitoring using contextual information assists health professionals in the decision-making process, which in turn, improves quality of life of the monitored patients. It provides a platform for healthcare professionals to assess the health status of patients in their care using multiple relevant parameters. This paper presented a context-aware decision support system for cardiac condition monitoring during rehabilitation. A federated learning approach was used to develop a model for activity recognition resulting in a better model that maintain users' privacy.

In future, the research will evaluate with real cardiac patients as previous experiment was conducted using healthy volunteers. Pilot to get feedback from the healthcare professionals and update the system is also in progress.

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